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Integration of stochastic process simulation and real time process monitoring of LCM

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Abstract

Liquid Composite Moulding (LCM) and its corresponding sub-processes of filling and curing involve several sources of uncertainty. The present study uses process conditions and material behaviour uncertainty measurements with Monte Carlo (MC) simulation to quantify the effect of variability on the final process outcome. Surrogate models of mould filling and curing based on Kriging have been constructed substituting Finite Elements (FE) solutions to achieve execution of the MC simulation with very small computational effort. Combination of stochastic simulation with on line monitoring results can narrow down gradually the envelope of possibilities predicted as the process progresses. This was carried out in this study using temperature and dielectric sensor signals and an inverse solution scheme based on Markov Chain Monte Carlo (MCMC). The integrated inverse solution is capable of predicting the process outcome with increased levels of certainty as the sensors uncover information gradually during the process. The use of surrogate models allows this solution to be carried out in real time in the manufacturing line.

Introduction

The manufacturing of composite materials incorporates several stages involving many dissimilar parameters presenting considerable variability [1]. This variability induces uncertainty in the manufacturing process affecting the outcome and quality of the final part. The variability can also initiate process defects resulting in rejected parts associated with considerable costs. Stochastic simulation methodologies have recently started to be developed to address the uncertainty in manufacturing processes and investigate its influence in process outcomes such as filling patterns, cure time, geometrical distortion and temperature overshoot.

The impregnation stage constitutes a complex process in which the presence of variability in boundary conditions and material properties may lead to significant variations in filling time and also in defects such as dry spots and voids. The permeability of textiles is a crucial process parameter that controls the filling step in liquid composite moulding. Evaluating the permeability of fabrics and its variability is critical as this parameter controls the occurrence of potential problems during impregnation stage such as dry spots formation, non-uniform filling and resin rich zones [2]. Variations in fibre architecture due to handling and storage, nesting effects during lay-up, fibre misplacement in the mould affect significantly permeability values introducing variability [3-5]. Permeability can show significant variations at the macro and micro scale [6,7]. In the mesoscale level (unit cell size) permeability variations can be represented by a log-normal distribution in the case of random mat [8]. Measurements of permeability have shown that its coefficient of variation can reach up to 20% [5,8,9]. Stochastic simulation of LCM has shown that variability of as resin viscosity, preform permeability and length of the distribution medium can introduce up to 15% variance in filling time [10]. It has been observed that variations in by-pass paths permeability result in high scatter in dry spot content [11]. Race tracking is a phenomenon referred to as an edge effect caused by imperfect placement of preform in the cavity of the mould. As a result, channels with high permeability can be formed along the edges, where flow front speed is increased significantly [12]. Statistical analysis has demonstrated that the permeability values caused by race tracking can be represented by a Weibull distribution [13]. Computational time is a significant factor governing the feasibility of stochastic simulation.

Flow process monitoring techniques have been developed to monitor critical parameters such as flow front position and to identify potential defects. Lineal sensors have been used to monitor complex flow fields in liquid moulding as well race tracking effects based on strategic positioning [14,15]. Process monitoring can provide real time information to process modelling to improve its predictive capability.

This paper aims at the uncertainty quantification of an epoxy resin viscosity and investigation of its influence on flow process outcomes. A series of rheology tests were carried out to characterise the viscosity variability of an epoxy resin. An existing viscosity model was used to represent the resin viscosity behaviour and also to estimate the statistical properties of model parameters. A Monte Carlo simulation coupled with a Finite Element model was implemented in the case of a plate to investigate the effect of viscosity uncertainty and others input parameters on variability on filling time. An inversion procedure based on Markov Chain Monte Carlo method has been developed integrating flow monitoring data with flow process modelling in order to narrow down process outcomes uncertainty estimation.

Methodology

Flow model description

A simulation of the filling stage considering heat transfer phenomena in a RTM process was implemented using the Finite Element software PAM-RTM®. The reinforcement material was Hexcel G0926 woven carbon fabric and the resin system was Hexcel RTM6 epoxy. In the RTM process the flow of the resin is modelled using Darcy's law. The flow model presented in Figure 1 comprises a flat panel with a rectangular insert. Boundary conditions of injection pressure ports and vents and constant temperature on the nodes in contact with the mould have been applied. The preform comprises 9 layers and has a compacted thickness of 3.3 mm resulting in a volume fraction of 56.7%. The filling was carried out at a constant temperature of 120 °C under a pressure of 2 bar with the simultaneous application of vacuum applied at the inlet and outlet positions respectively.

The viscosity model implemented in this study utilises the viscosity at a reference temperature η_0 as a state variable [16]. The reference viscosity follows its own kinetics and can be expressed as follows:

$$\frac{d\ln\eta_0}{dt} = Ae^{-\frac{E}{RT}}(\ln\frac{\eta_0}{\gamma})^m \tag{1}$$

The rate of change of the reference viscosity in Eq. (1) follows an Arrhenius dependence on temperature T where A is the pre-exponential factor whilst, E is the activation energy of Arrhenius function. The dependence of the rate of change on the logarithmic of reference viscosity has an autocatalytic behaviour with m denoting the order of this dependence and γ a coefficient.

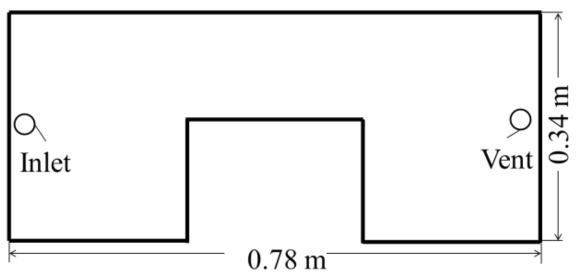


Figure 1 Flow model geometry

The viscosity at any temperature can be estimated, using the reference viscosity calculated by the integration of Eq. (1), as follows:

$$\eta = \eta_0 A e^{-D(\frac{1}{T} - \frac{1}{T_0})} \tag{2}$$

where T_0 denotes the reference temperature and D is the temperature dependence coefficient.

Uncertainty quantification experiments

Rheology tests of Hexcel RTM6 epoxy resin were carried out using a TA Instrument AR200ex rheometer. Cyclic thermal profile tests were conducted in this study as illustrated in Figure 2. This includes cycles of cooling and heating applied during periodic interval in the interim of an isothermal experimental at the highest temperature (120 °C). The cycle has a magnitude of 40 °C resulting in a minimum temperature of 80 °C, whilst the ramp rate for both heating and cooling phases was 10 °C/min. The samples in this test weigh approximately 1 g.

Samples from four different batches were utilised. All batches were within the shelf life at the time of testing stored in the fridge conditions as is recommended by the manufacturer [17]. More specifically, the resin is allowed to remain at ambient temperature and -18 °C up to 15 days and 9 months respectively. Therefore, two different tests for each batch were conducted at the 1st and the 15th day of ambient temperature exposure.

Stochastic simulation

The stochastic simulation is based on Monte Carlo (MC) and involves the generation of N realisations of random input stochastic variables. The MC sampling points are generated using a set of normally distributed uncorrelated random variables. The random variables considered in this study were initial reference viscosity, principal permeabilities and tool temperature. In each realisation, the flow model is executed calculating the filling time and subsequently computing their first and second statistical moments using the overall set of realisations. A total of 400 realisations are required to ensure convergence in average and standard deviation. The outputs of the stochastic simulation are the average and standard deviation of filling time. The implementation of stochastic simulation was carried out in Visual Studio C++

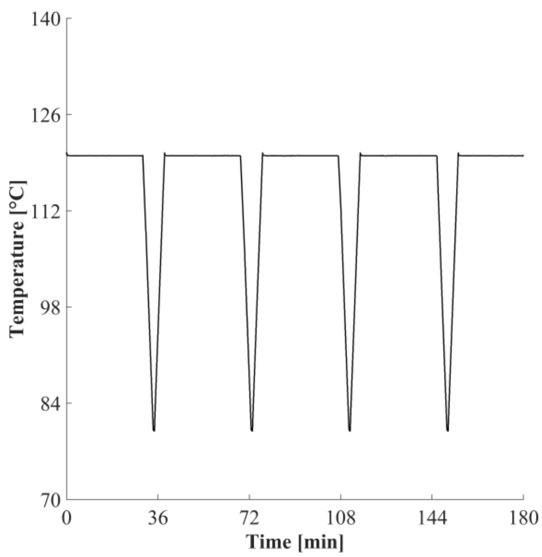
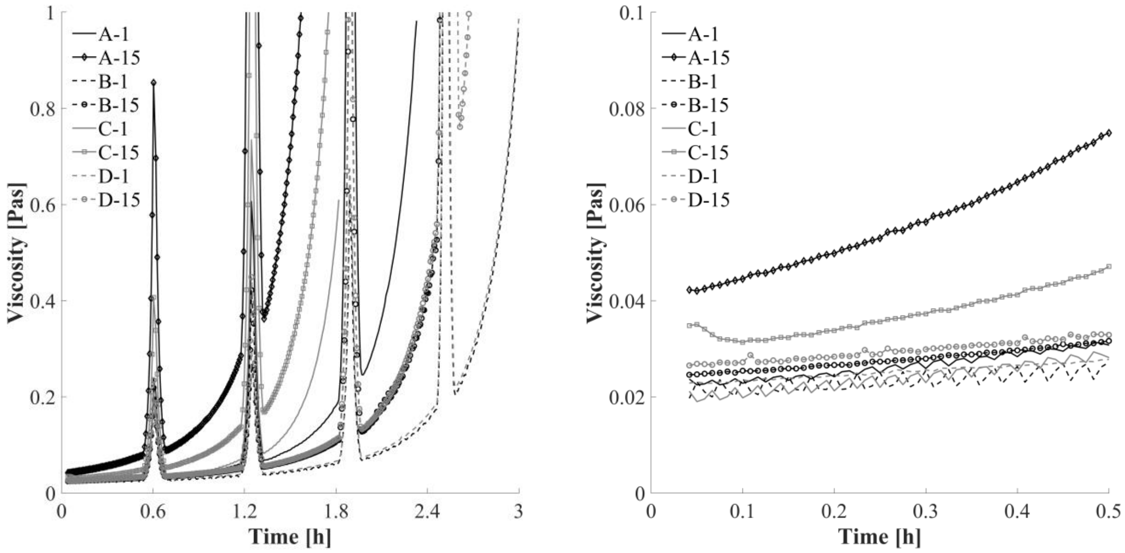


Figure 2 Cyclic thermal profile



a) b)

Figure 3 a) Viscosity results for different batches and different storage conditions b) Detailed view of viscosity results.

Results

<u>*Uncertainty quantification*</u>

Experimental results for the resin viscosity are presented in Figure 3. All curves present the same qualitative behaviour comprising parts that are controlled by material state changes (isothermal sections) and parts controlled by temperature elevations (cooling/heating cycles). The viscosity increases with time due to the increasing cross linking density in the thermosetting material and increases/decreases with the cooling/heating applied to the sample.

Significant variability can be observed both in the comparison between batches and between different days of exposure at ambient temperature as illustrated in Figure 3b. The batch to batch variability can be attributed to variations in thermal history due to different resin handling/ storage conditions. The initial viscosity of the resin samples stored longer at ambient temperature is higher and increases faster with time than samples with shorter exposure in ambient conditions. T

Fitting of the viscosity model presented in Eq. (1-2) on each rheology test was performed leading to the computation of the first and second statistical moments of each parameter. Also, the initial reference viscosity η_∞ was estimated. In this case, the reference viscosity is calculated at the reference temperature T_o=80 °C.

Table 1 Statistical properties of stochastic variables

	Average	**Standard deviation**
Initial reference viscosity (η_∞)	0.17 Pas	0.03
Principal permeability (K_1) [5]	1.7E-11 m^2	3E-12 m^2
Principal permeability (K_2) [5]	1.3E-11 m^2	2.5E-12 m^2
Tool temperature (T) [18]	120 °C	1.67 °C

The initial reference viscosity η_∞ presents the highest variability among the parameters. Initial reference viscosity η_∞ variability can be attributed to the different initial material state of each sample due to the different duration of exposure at ambient temperature. The distribution of the stochastic variable η_∞ can be treated as uniform assuming that the probability of resin usage within the permitted time range is equal for each day. Table 1 summarises the stochastic variables and their statistical properties considered in stochastic simulation and includes initial reference viscosity, principal preform permeabilities [5] and tool temperature [18].

Stochastic simulation

The average and standard deviation evolution of filling time are illustrated in Figure 6a. The mean value converges after 80 iterations to 40 min whilst the standard deviation reaches a plateau of about 13 min after 300 realisations. The filling time presents high variability with a coefficient of variation of about 30%. This can be attributed mainly to the significant variations of the initial state of resin viscosity. Fabric imperfections, storage conditions and hand lay-up lead to different preforms architectures in each realisation resulting in significant variations of the principal permeabilities. Also, tool temperature uncertainty affects resin viscosity resulting in filling time variations.

Inversion procedure

The high variability of process outcomes of filling process due to input parameters and boundary conditions variations can be narrowed down using an inversion procedure integrating flow model with process monitoring data. The inversion procedure presented schematically in Figure 5 is based on the Markov Chain Monte Carlo (MCMC) method and integrates flow monitoring data with the flow model. MCMC operates as a sampler drawing a series of realisations of unknown stochastic parameters (in this case principal permeabilities, edge permeability and initial resin viscosity) with a probability of acceptance proportional to the conditional incremental likelihood of process monitoring results. The accepted realisations constitute the solution of the inverse problem in the form of a probabilistic estimate of process outcomes. Inversion requires a high number of iterations for convergence and thus the use of FE model is computationally unfeasible. Therefore, a computationally efficient surrogate model of the filling stage of RTM was developed based on Kriging applied to a set of results produced using Finite Element (FE) analysis. Figure 6b presents the filling time evolution as estimated by inversion procedure. The mean value converges to 34 min whilst the standard deviation 0.4 min. Compared to stochastic simulation results the variability of filling time estimation was reduced by 95 % highlighting the robustness of the inversion analysis.

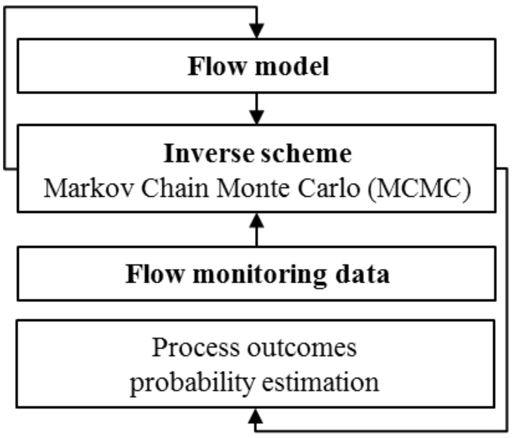


Figure 4 Inversion procedure framework.

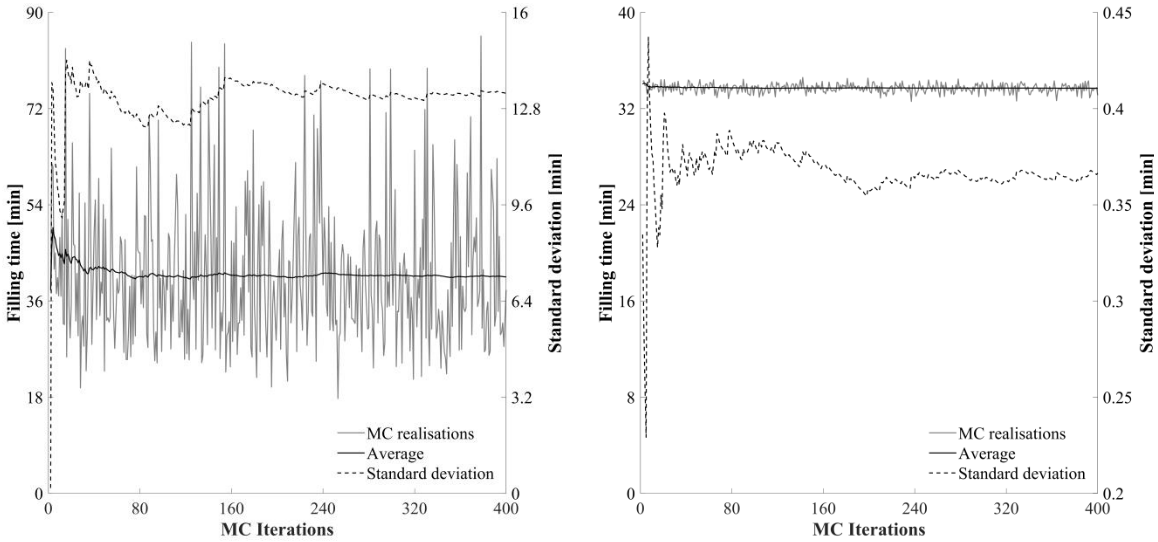


Figure 5 a) Stochastic simulation of flow stage results. b) filling time uncertainty estimation with inversion analysis.

Conclusions

The presence of uncertainties in material properties and boundary conditions result in high variability on process outcomes affecting significantly final product quality. It was found that different exposure days of epoxy resin at ambient temperature alters initial state of resin viscosity. This along with principal permeabilities and tool temperature variations affect the duration of filling process presenting a coefficient of variation of about 30%. An inversion procedure has been developed in order to narrow down this variability integrating the flow model with process monitoring data to estimate in real time the process outcomes such as the filling time during the impregnation. In a demo case of a rectangular plate the utilisation of inversion scheme narrowed down uncertainty estimation of filling time by 96%.

Acknowledgments

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